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A Colour Iris Recognition System Employing Multiple Classifier Techniques

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Abstract

The randomness of iris texture has allowed researchers to develop biometric systems with almost flawless accuracies. However, a common drawback of the majority of existing iris recognition systems is the constrained environment in which the user is enroled and recognized. The iris recognition systems typically require a high quality iris image captured under near infrared illumination. A desirable property of an iris recognition system is to be able to operate on colour images, whilst maintaining a high accuracy. In the present work we propose an iris recognition methodology which is designed to cope with noisy colour iris images. There are two main contributions of this paper: first, we adapt standard iris features proposed in literature for near infrared images by applying a feature selection method on features extracted from various colour channels; second, we introduce a Multiple Classifier System architecture to enhance the recognition accuracy of the biometric system. With a feature size of only 360 real valued components, the proposed iris recognition system performs with a high accuracy on UBIRISv1 dataset, in both identification and verfication scenarios.

Key Words: Colour Iris Recognition, Multiple Classifier Systems, Principal Component Analysis.

1 Introduction

The richness and randomness of the iris texture were suggested as potential biometric identification means back in 1980s by Drs Flom and Safir. The first implementation of an iris recognition system capable of an automatized authentication was done by Prof John Daugman in 1994, at Cambridge University [1]. Since then, a large number of iris recognition methods have been developed, most of them reporting very high accuracies [2-4], but they are only able to operate on images acquired under near infrared illumination.

Under near infrared illumination, the melanin pigment, where all the reflections are captured in visible spectrum, is not stimulated, thus the iris structure is revealed. Reflections are one of the main noise factors in colour iris images [5], as they obstruct areas of the iris texture. In a classical iris recognition system, the near infrared illumination implies a series of user constraints: the subject has to be in the field of view of the near infrared illumination and has to look for a few

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seconds at the acquisition device [6]. Together with the high cost of the near infrared iris acquisition devices, the practicability of a near infrared iris recognition system is significantly decreased.

Colour iris recognition may be a controversial topic. On one hand, since the majority of currently deployed iris recognition systems use near infrared illumination, there are large near infrared iris databases and the colour iris recognition is considered in [7] to "counter to the approach used by all commercial systems … and also counter to the majority of academic research". On the other hand, as the mobile phones and tablets become more computationally capable and the need of biometric authentication on this type of devices is apparent, is necessary that colour iris recognition algorithms be deployed on such common devices. Mobile phone applications, like BioWallet [s] are capable of signature recognition and iris recognition.

One of the pioneers of iris recognition in visible spectrum is Hugo Proenca, who organized a colour iris recognition competition called Noisy Iris Challenge Evaluation (NICE). It took place in 2 parts: part1 assessed only the segmentation of a subset of UBIRISv2 dataset and in part 2 the classification algorithms were assessed on the same images. The winning algorithm of part 1 is described in [8] and the best algorithm from part 2 is presented in [9]. Proenca et al analyzed the results of the second part of NICE competition in [10], and they reported that by employing a multi-algorithmic approach between the top 5 ranked algorithms, the accuracy of the system increased significantly. The above mentioned competition had numerous participants from all over the world, which indicates that researchers are focusing more and more on colour iris recognition.

In this paper we extend the work from [11], where Multiple Classifier Systems (MCS) were employed in the classification phase of a colour iris recognition system. The main contribution of [11] was the database-free operation of an iris recognition system, by using Multiple Classifier techniques. In addition to the contributions presented in [11], this paper distinguishes itself by:

- Presenting the details of the Multiple Classifier System design;
- Comparing the experimental results when 50% of the iris texture is used with the results obtained when 100% of the iris texture is used.

The eye colour is one of the properties that are most noticeable and easy to remember when we describe an individual. Although the accuracies of visible light iris recognition systems are not yet comparable to those of near infrared iris recognition systems, eye colour (i.e. area around the iris) [12] cannot be used in near infrared spectrum as a soft biometric. The advantages and disadvantages of iris recognition under near infrared and visible illumination are summarized in table 1.

	Advantages	Disadvantages
Near infrared	- Almost perfect accuracy claimed on images acquired in enrolment stage, with supervision; - 0 false accept rate, due to the rapid termination of impostors' distribution; - Low template size; - Computationally efficient;	- Not designed to cope with noisy iris images; - Requires a high degree of cooperation from the user due to the near infrared illumination; - Images are acquired using expensive acquisition cameras; - Decreased practicability;
Colour	- May be implemented on common hardware, as laptops or mobile phones; - Cheap acquisition cameras; - Increased practicability; - May use eye colour as soft biometric;	- Lower performance compared to near infrared iris recognition systems; - Strong noise present in the images due to melanin pigment;

Table 1: Advantages and Disadvantages of near infrared and colour iris recognition

The remainder of this paper is organized as follows: in section 2 the iris image preprocessing is detailed. In section 3, the feature extraction is explained and the proposed Multiple Classifier System design is described in section 4. The experimental results are reported in section 5 and conclusions are given in section 6.

2 Iris Image Preprocessing

An iris recognition system is composed of 5 main stages: acquisition, segmentation, normalization, feature extraction and matching. In colour iris recognition systems, the segmentation requires a significant computational effort [8], as a correct localization of the iris is vital for further stages of the biometric system. If the feature extraction and classification stages are computationally demanding too, the iris recognition system will have a decreased usability, especially if it is to be deployed on mobile or embedded devices. Therefore, a simple method for feature extraction and a robust classification stage are essential for a practical implementation of a colour iris recognition system, especially in mobile platforms.

For the segmentation phase, the algorithm proposed in [13] was used. For iris detection, the red channel of the image was used and for the pupil detection, the red channel together with the hue and saturation channels from HSI colour spaces were used. The very noisy images, which could not be correctly segmented automatically, were segmented manually. On approximately 7% of the images the employed segmentation algorithm failed. The noise detection is a time consuming process in an iris recognition system [8], particularly if the biometric system is designed for mobile devices. In the proposed approach, no noise removal or eyelid/eyelash detection method has been applied.

The images were normalized using the rubber sheet model proposed in [1]. To avoid including the eyelashes and eyelids in the unwrapped image, the sector defined between -45^{o} and +45^{0} of vertical axis in the top half of the iris was discarded in the normalization process. The obtained unwrapped iris image size is 360 by 100 pixels. A method based on information theoretic analysis of iris texture, which shows how to determine which channels from RGB and HSI colour spaces reveal useful information is presented in [14]. According to this method, the red and green channel from RGB colour space and intensity channel from HSI colour space contain the most discriminant information. The iris images were unwrapped therefore from the red, green and intensity channels and all the three channels were further used for feature extraction and classification.

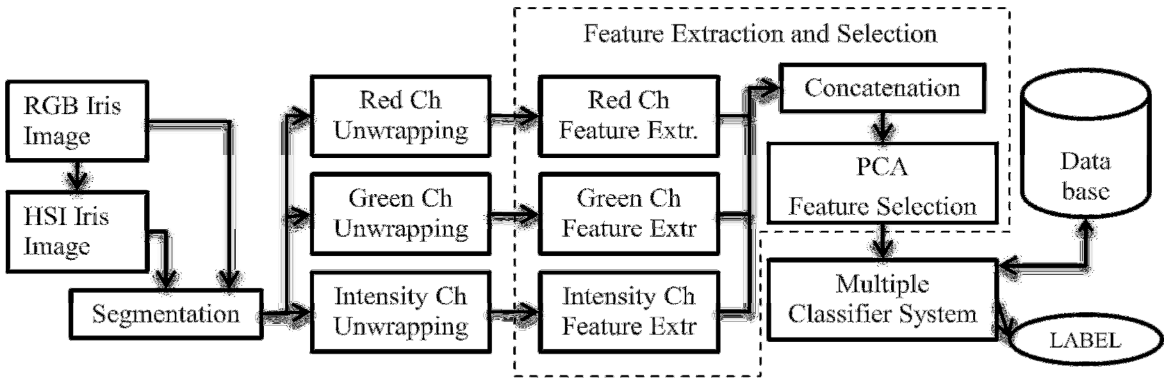


Figure 1. Proposed Iris Recognition System

For UBIRISv1 [20], the iris image database that we used in our experiments, the average diameter of the iris is approximately 350 pixels and the average width of the iris band is approximately 100 pixels. In our previous work [11], which we extend here, only 50 pixels around the pupil were used, with a size of the unwrapped image of 360 by 50 pixels. By considering 50 pixels around the pupil, in the case of UBIRISv1 database, only 50% of the available texture is used. By using 100 pixels around the pupil, we are able to analyse how the performance of the proposed colour iris recognition system is changing when the amount of the available information doubles from approximately 50% to 100%.

No image enhancements techniques were applied on the unwrapped iris image, in order to reduce the computational demand for a possible embedded or mobile implementation. In the system's block diagram from Figure 1 the preprocessing steps may be observed.

3 Feature Extraction

A bank of circular symmetric filters is used in [4] to extract a real-valued feature vector of length 384. The experimental results reported using these features were comparable to the best results reported in the literature on near infrared images. Circular symmetric filters are similar to 2D Gabor filters [1], being the product of a Gaussian envelope and a sinusoidal function. The difference between the two types of filters is that 2D Gabor filters are complex-valued and have an orientation for the sinusoidal function, while the circular symmetric filters only have a real part and no orientation. The circular symmetric filters have the form given by equation (1):

$$G(x,y,f)=\frac{1}{2\pi\delta_x\delta_y}e^{-\frac{1}{2}\left(\frac{x^2}{\delta_x^2}+\frac{y^2}{\delta_y^2}\right)}cos\left(2\pi f\sqrt{x^2+y^2}\right) \quad (1)$$

where δ_x and δ_y are the space constants of the Gaussian function, f is the frequency of the modulating sinusoid. The window size of the filter to be applied is the fourth parameter necessary to be found. The reason why circular symmetric filters are used over classical 2D Gabor filters is that in a small rectangle of the iris texture, the orientation of the texture is not relevant, as explained in [4]. Moreover, 2D Gabor filters are less computationally efficient than circular symmetric filters because they have an imaginary part, while circular symmetric filters only have the real part.

Similar to the method proposed in [4], the unwrapped iris image is convoluted with the circular symmetric filter and the obtained image is divided into 10 by 10 pixel rectangles. Subsequently, for each 10 by 10 window, the mean and mean absolute deviation is computed. As the unwrapped image size is 360 by 100, there are in total 36*10*2=720 real valued components for one channel. This process is run for red, green and intensity channels, resulting in a raw feature of size 2160. The issue of alignment is addressed by rotating the unwrapped probe image 3 pixels to the left and 3 pixels to the right and extracting the features every time.

Genetic Algorithms (GA) were employed to search the 4 parameters of the circular symmetric filters [15] from equation (1). The fitness function employed was the mean rank 1 identification accuracy over three repetitions with randomly chosen probe and gallery images from the first 40 classes from UBIRISv1, Session 1 dataset. 4 random images are used for training and 1 for testing from each class. If the mean identification rate is above 95%, the parameters are considered satisfactory and are saved. The mutation function of the GA adds a random vector from a normal Gaussian distribution to the parent. The crossover function of the employed GA creates the child as a random weighted average of the parents.

Unlike in a classical iris recognition system [1], where only a distance is computed between a probe and gallery image, we employ classifiers in the matching phase of the biometric system. A classifier is a method that realizes the mapping between the input features and the corresponding output class labels [16]. Before it can output a class label, a classifier needs to be trained. As the features used by the proposed biometric system are extracted from 3 colour channels, they contain redundant information and will be highly correlated. We have applied Principal Component Analysis (PCA) to reduce the correlation between the features and in the same time the feature dimensionality. After that, a number of generic classifiers were trained and used in the fitness function of the GA to determine which classifier performs better.

The rationale behind this approach is to obtain a population of useful sets of parameters of the circular symmetric filters using the GA. Subsequently, features obtained using selected sets of parameters will be used to train the base classifiers, which will be subsequently combined in a Multiple Classifier System to enhance the system's accuracy. The final feature size, obtained by applying PCA was reduced from 2160 components to only 360 components, as it will be shown in Section 4.

4 Multiple Classifier System Design

The combination of multiple classifiers is an efficient method to enhance the accuracy of a biometric system [17]. A MCS can be built with two main strategies [21]: 1) *fusion*, where each individual classifier is supposed to have knowledge of the whole feature space and the decision is agreed by all of them; 2) *selection*, where each individual classifiers is an expert only in a part of the feature space and plays a more important role in the final decision. The iris recognition system proposed in this work employs a MCS built with a fusion of the decisions of the base classifiers.

By training the individual classifiers on features extracted using different sets of parameters of the circular symmetric filters, we aim to build a MCS where the component classifiers make diverse [18] decisions when an input feature is processed. In this way, if some of the samples are misclassified by some classifiers, it is likely that they are correctly classified by a larger set of classifiers from the ensamble, thus increasing the accuracy of the MCS.

4.1 Design Steps

The first step in the design of the proposed MCS was to determine what base classifier works best and what is the optimum PCA dimension of the features extracted from the three colour channels. The parameters of the circular symmetric filters were searched using GA for 6 base classifiers: Linear classifier, Fisher classifier, Nearest Neighbor classifier, Parzen classifier, Tree classifier and Support Vector Machine classifier [25]. The optimum rank 1 identification accuracy obtained by the GA for each classifier on 40 classes from UBIRISv1, session 1 dataset, for different PCA dimensions may be observed in the 3D bar plot from Figure 2.

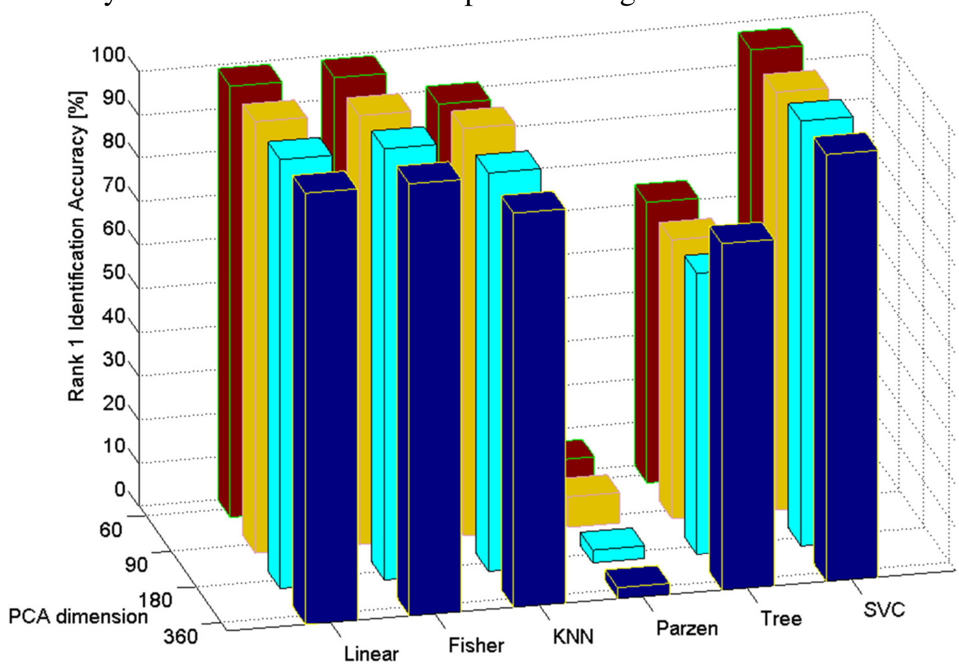


Figure 2. Performance of 6 base classifiers on 40 classes from UBIRISv1, Session 1 dataset

To find which base classifier is the most appropriate to be used, the 6 base classifiers were employed using the feature selection made by PCA. From the original 2160 dimensions, the PCA was applied to reduce the number of dimensions to 360, then 180, 90 and finally 60. From Figure 2 we observe that Linear and Fisher classifiers perform best for a range of different number of dimensions after PCA was applied. The third place was obtained by the Support Vector Classifier, but this classifier requires a significantly larger time for training compared to Linear and Fisher classifiers. Support Vector Classifier is not suitable for a mobile or embedded implementation of the iris recognition system.

The second step in designing the MCS is to determine whether Linear or Fisher classifiers has to be chosen to increase the MCS's accuracy. A desirable property of a MCS is to include component classifiers which do not make the same errors on a given set of test samples. After the GA runs for a given classifier, it finds multiple sets of parameters for which the fitness function has a minimum value. By training the same type of base classifier separately on features extracted using different parameters of the filters, we aim to observe if the errors are different from one classifier to another.

We trained 2 Fisher classifiers and 2 Linear classifiers on features extracted from the same iris images using different parameters. Then, the trained classifiers were tested on the same 40 images. For each of the 40 images, we formed a binary vector which on one position takes the value of 0 if the corresponding image was correctly classified and 1 if the corresponding image was not correctly classified. Subsequently, to observe if the errors are different for the same type of classifier, we performed an exclusive or operation between the two binary vectors corresponding to the Fisher classifiers and then for the vectors corresponding to the Linear classifiers. By suming the components of the obtained binary vectors we are able to see which of the two types of classifiers makes different errors. A large value of the sum means that the classifier is making different decisions for feature extracted using different parameters. This process was repeated 25 times for 1 randomly chosen test and 4 train samples and the final values of the sums corresponding to the 2 classifiers are the average of the 25 runs.

We found that the average sum of the binary vectors obtained after the exclusive or operation was 0.6 for the Fisher classifier and 1.7 for the Linear classifier. The average sums' values indicate that Fisher classifiers trained on features extracted different parameters of the circular symmetric filter misclassify the same images, while Linear classifiers make different errors. Therefore, the Linear classifier will be chosen as a base classifier of the MCS.

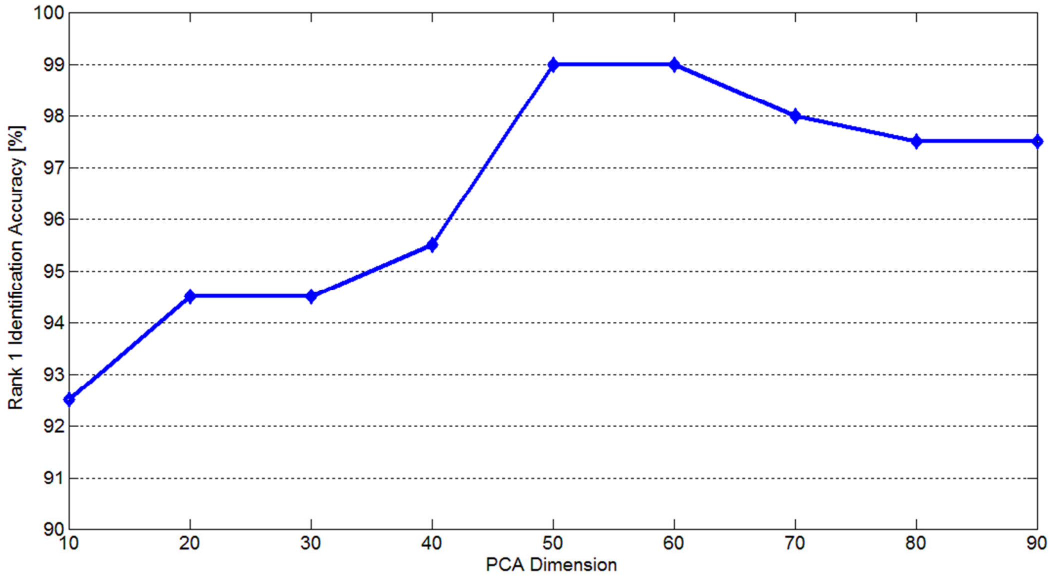


Figure 3. PCA Dimension vs Identification accuracy for Linear classifier

To optimize the feature dimension obtained by using PCA, we ran the GA for various PCA dimensions using the Linear classifier. In Figure 3 the rank 1 identification accuracies are plotted for the optimum solution found by the GA when the dimensionality of the features is decreased. As it is shown in Figure 3, the identification accuracy of the Linear classifier is decreasing when the number of dimensions drops below 50. However, the number of solutions found by the GA that are above the 95% identification threshold was higher for a PCA dimension of 60. Thus, the optimum PCA dimension for the proposed iris recognition system is 60.

The third step in the design of the proposed MCS is to find the optimum number of the base classifiers and the appropriate fusion method for the posteriors of the component classifiers. In a MCS, the module that combines the outputs of different base classifiers is usually called *combiner*.

If the combiner does not require separate training, then it is called a *non-trainable combiner*. If the combiner needs to be trained before it can be used, then it is a *trainable combiner* [19].

Initially we took two linear classifiers trained on features extracted using different sets of parameters of the circular symmetric filter. 6 non-trainable fusion methods for the posterior probabilities of the base classifiers were tested: average, product, majority voting, minimum, maximum and sum. This process was repeated for 25 times with randomly chosen train and test images and the average of the 25 runs was obtained for all the fusion methods. Subsequently, the number of base classifiers was incremented by 1 and the sequence of operations metioned above were executed. As the identification accuracy of one Linear classifier is approximatively 99%, there is no much place for improvement, therefore we ran the experiments on all the classes of UBIRISv1 Session 1 dataset, keeping 4 random images for training and one for testing for each iteration.

We observed that the best performing fusion method was the average and by adding more than 6 base classifiers, the accuracy of the MCS will not increase, as shown in the experimental results section. The usage of 6 base classifiers to build the MCS implies that the final feature size will have 360 real valued components. The architecture of the designed MCS is illustrated in Figure 4 for the verification scenario. As it may be observed from Figure 4, the structure of the MCS is augmented with 2 distance matchers, a Hamming distance matcher and a Pearson Distance (PD) matcher.

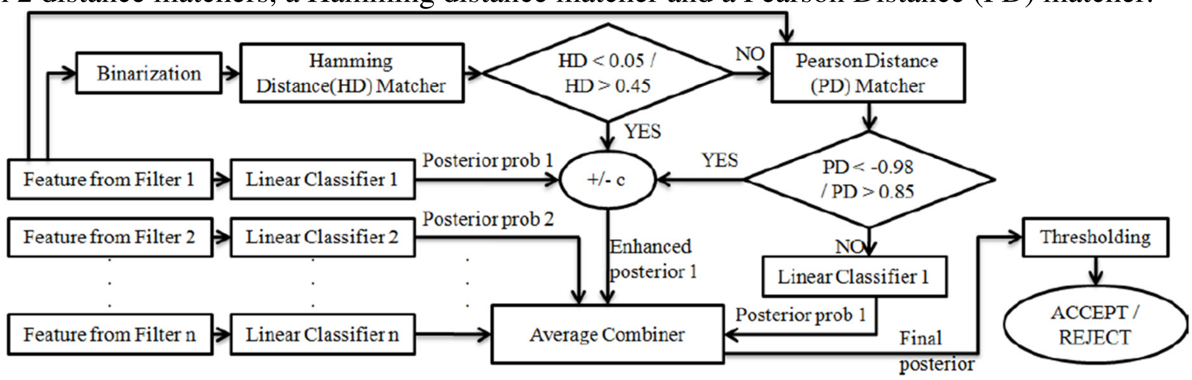


Figure 4. MCS architecture for verification scenario

The logic of the MCS augmented with the distance matchers is the following: one of the n input features (in Figure 4 feature 1) obtained with different filters is binarized by comparing the 60 real values with their median value. If a feature component is greater than the median value, then the corresponding binary component will be a logical one, otherwise a logical 0. Then, a HD is computed between the probe and gallery features. If the HD is considerably low (less than 0.05 in our implementation) or considerably high (greater than 0.45 in our implementation), then the posterior probabilities of the linear classifier corresponding to that particular feature is increased or decreased by a constant c. If the HD is between the low and high certainty thresholds, a PD is computed between the 60 components gallery feature and its corresponding probe feature.

PD is a similarity measure of two sets of real values, having the form given by equation (2):

$$PD = 1 - 2\frac{Z(X) \cdot Z(Y)}{N} \quad (2)$$

It may be observed that the numerator of the fraction in equation (2) is the dot product between the standard errors of the 2 vectors X and Y and N is the size of the vectors X and Y. Again, if the PD of probe and gallery features is below a threshold (-0.98 in our implementation) or above a threshold (0.85), then the posterior of the linear classifier corresponding to that particular feature is increased or decreased by a large constant c.

The 2 distance matchers are used to provide complementary information to the Linear classifiers in order for the MCS to take a correct decision. The accept /reject decision is taken by thresholding the final averaged posterior outputted by the average combiner. Before thresholding, the final posterior probability is inverted and normalized to be in the range [0 1], where the values close to 0 suggest that the probe and gallery images are from the same class and a value close to 1 means a non-match. It is interesting to observe how the MCS performs in the verification scenario when different features out of the 6 are chosen to be processed by the distance matchers. Also, it is desirable to see if the addition of the distance matchers improves or not the verification accuracy of the iris recognition system. These analyses will be made in the experimental results section. In the identification scenario, the outputs of the Linear classifiers are averaged and the class label corresponds to the class with the largest average posterior probability.

4.2 Discussion

The most significant advantage of using MCS for identification scenario of any biometric system is that once the base classifiers have been trained, there is no need to query the database when identifying a user. Therefore, a MCS approach for identification scenarios of an iris recognition system is beneficial due to the following three reasons:

1. The issue of database security on an operational device disappears.
2. On large scale databases (millions of users), the time needed to identify a subject is significantly reduced compared to a system which uses classical binary features and HDs. This is a valid observation, since the time of accessing the templates on the storage devices is eliminated.
3. The biometric system becomes suitable for embedded and mobile applications.

The disadvantage of using a MCS approach in an iris recognition system is that the base classifiers have to be retrained every time one user is enrolled in the database. In a classical iris recognition system, where only distances are computed between the probe and gallery images, enrolling a new user is not an issue. However, a distance based matching does not yield an acceptable accuracy for noisy colour iris images, as shown in [14]. Thus, a trade-off between a matching-based (near infrared) iris recognition system and a MCS-based (colour) iris recognition system has to be made according to the application for which the biometric system is designed.

A MCS approach is more appropriate for biometric authentication in industry or institutional environments, where there are a few hundred users and there is no need to enrol users in the database every day. Also, the financial resources of such organizations are often limited, but a high performing colour iris recognition system is an affordable biometric authentication system. A near infrared iris recognition system with a distance-based matching is suitable for border control environments, where there is no tolerance for false matches.

5 Experimental Results

The efficiency of the proposed iris recognition system is benchmarked on UBIRISv1 database [20]. This database consists of 1867 colour RGB iris images with a dimension of 800x600 pixels. The images were collected from 241 individuals in 2 sessions. The users are enrolled by acquiring 5 images of their right eye. In the first session the images are captured by minimizing noise factors. In the second session the environment is one with reduced constraints and strong noise factors are present in the images, such as reflections, occlusions, luminosity variations and poor focus. In the first session, all 241 users have been enrolled, resulting in a total of 1205 images, while in the second session, only 132 users out of the 241 are enrolled.

5.1 Experimental Setup

Both verification and identification scenarios were explored in the experiments. For all the experiments 4 out of 5 images from each class were used as gallery, and one as probe. The probe image from each class was chosen randomly. All the experiments were carried out separately for Session 1 and Session 2 of the UBIRISv1 database. One random probe image from each class is used in the identification scenario to obtain the rank 1 identification accuracy. This process is repeated 100 times and the final rank 1 identification accuracy is the mean of the 100 runs.

In the verification scenario four random gallery images are kept in the database for all classes. Then an unseen probe image, randomly chosen, claims to have a certain identity and the obtained posterior probability corresponding to the claimed class label is compared with a threshold. The False Accept Rate (FAR) and False Reject Rate (FRR) were computed for 90 values of the threshold, within interval [0.1; 1] and for each step the current threshold was obtained by adding to the previous threshold 0.01. This process is repeated 100 times and the FAR and FRR for every value of the threshold is the average of the 100 runs. The Equal Error Rate (EER) is obtained for the threshold where FAR and FRR have approximately equal values.

The experiments were conducted using 100 pixels around the pupil and the obtained accuracies are compared to the results obtained in [11], where only 50 pixels around the pupil were used.

5.2 Identification Results

The base classifiers are trained on features extracted using different parameters of the circular symmetric filters, as explained in section 4. Initially we ran the experiments for identification scenario for different numbers of base classifiers, to find the optimum number of Linear classifiers needed in the design of the MCS. The base classifiers were trained on 4 random iris images from all classes of UBIRISv1 Session1 dataset and tested on the remaining image from each class. The process was repeated 25 times and then the number of the base classifiers was incremented. In the box plots from Figure 5 we may observe how the rank 1 identification accuracy increases with the number of base classifiers. By analysing Figure 5, we conclude that the optimum number of base classifiers is 6. Also, it may be observed from the same figure how the stability of the biometric system increases as more classifiers are added to the ensemble.

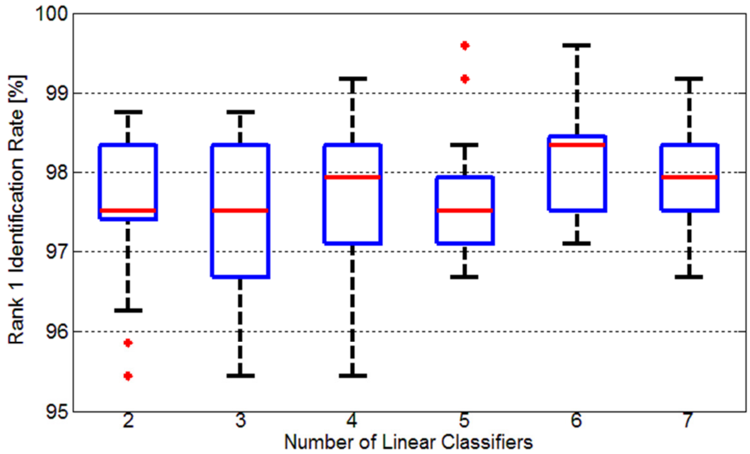


Figure 5. Rank 1 identification accuracy for different number of base classifiers

In [11], where 50 pixels were used around the pupil, the red channel showed a slightly higher rank 1 identification accuracy than the fusion of red, green and intensity channels, but only on the iris images from Session 1, which are good quality. This may be due to the fact that the red channel has the closest wavelength to the near infrared spectrum, thus the noises such as reflections are not affecting significantly the red channel. On the second session, where the images contain more noise factors, the fusion between the three channels performed better than the red channel.

Initially all the images from the two sessions are used in identification scenario. In Session 1, 10 are strongly or totally occluded, therefore, no useful iris information can be extracted from them. From Session 2, 13 images out of 662 are strongly occluded. The occluded images were manually detected. To assess more objectively the system's performance, we added a reject option to the MCS, so that when an occluded image is chosen as probe, the system ignores it without counting a transaction. However, the occluded images are used in the training stage of the MCS.

In Table 2, a comparison between the mean rank 1 identification accuracies obtained using 100% and 50% of the available iris texture is made, when all the iris images from the database are used and when the occluded images are rejected. From Table 2 we observe that the fusion performs better than the red channel when 100 pixels around the pupil are used, for both sessions.

Method \ Iris texture usage	Session 1		Session 2	
	50%	100%	50%	100%
Radu et al [14]	99.25 %	-	91.96 %	-
Proposed using red channel	98.10 %	97.15 %	87.26 %	92.67 %
Proposed using fusion	97.63 %	98.20 %	90.03 %	95.43 %
Proposed using fusion and rejection of occluded images	98.38 %	99.17 %	91.18 %	95.79 %

Table 2. Rank 1 identification accuracy of the proposed biometric system

It is interesting to see how the system performs in identification scenario, when no PCA is used to reduce the redundancy of the iris features components. We conducted the computationally demanding experiments for all the images from Session 2 with the option of rejecting the occluded images enabled. The feature size becomes 2160 times 6, the number of base classifiers, which equals to 12960. The obtained mean rank 1 identification accuracy was 99.23% for Session 2. As far as we are aware, this identification accuracy is the highest one published in the available literature for UBIRISv1, Session 2 database. The robustness of the proposed iris recognition approach enables the biometric system to correctly classify images with significant amount of noise, among them being the images shown in Figure 6.

Figure 6. Noisy iris images from Session 2, correctly identified by the proposed iris recognition system

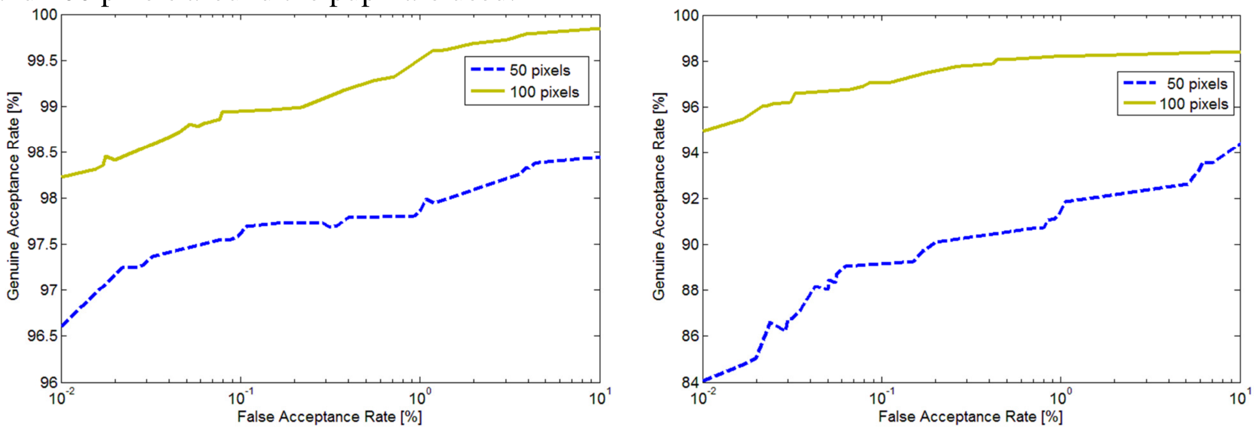
5.3 Verification Results

In the verification scenario, initially we tested whether the distance matchers improve the system's Equal Error Rate (EER) or not (see Figure 4). We took one of the 6 input features at a time and ran the experiments on all the images of Session 1 and Session 2 10 times. Then, we conducted the verification experiment for the case when the distance matchers are not included in the MCS architecture. The final EER was the mean of the 10 runs for every case. Table 3 summarizes the EER obtained for the above mentioned cases, when 100 pixels around the pupil are used.

Feature used as input for the distance matchers	Equal Error Rate [%]	
	Session 1	Session 2
Feature 1	3.86	5.36
Feature 2	4.18	4.78
Feature 3	3.70	5.40
Feature 4	3.69	4.65
Feature 5	3.81	4.98
Feature 6	3.78	4.55
None	3.75	4.69

Table 3. EER for different features used as input for the distance matchers

The data from Table 3 shows that there is no significant difference between the EER obtained using the distance matchers and the EER obtained when only the base classifiers are employed. Nevertheless, the system will be able to *operate in the verification scenario without the database*, once the base classifiers have been trained. The Receiver Operational Characteristic (ROC) curves for all the images from Session 1 and Session 2 are shown in Figure 7, for the cases when 50 pixels and 100 pixels around the pupil are used.



a) UBIRISv1 Session 1 b) UBIRISv1 Session 2

Figure 7. ROC curves when 50 pixels and 100 pixels around the pupil are used

The improvement brought by the usage of 100% iris texture is significantly larger on the low quality images from Session 2. In order to compare the EER with results published on the 2 sessions of UBIRISv1, we chose the work from [21], where approximately 7% out of the total number of the total images in the dataset were not used in the experiments. Also, in [21], the results are reported using 5 algorithms. In our experiments, we manually selected 7% of the most noisy iris images from Session 1 and 7% from Session 2 and we added a reject option for these images to the MCS, but the images were used in training. The comparison between the EER obtained using the proposed method and those reported in [21] is presented in Table 4.

Method	Session 1 EER [%]	Session 2 EER [%]
Poursaberi and Araabi [22]	2.1	5.0
Ma et al [23]	1.9	5.0
Rakshit et al [3]	1.2	3.8
Ahmadi et al [24]	1.9	8.0
Tajbakhsh et al [21]	0.4	3.0
Proposed, using 50% of the iris	1.2	6.7
Proposed, using 100% of the iris	0.2	1.8

Table 4. Comparison of verification error rates without 7% of the images

6 Conclusions

In the present work we present a robust iris recognition approach capable to deal with colour noisy images. Unlike the majority of the iris recognition systems available in the literature, which are employing a distance-based matching, the proposed method uses MCS in both verification and identification scenarios.

The architecture of the MCS consists of Linear classifiers trained on features extracted using 6 different sets of parameters of circular symmetric filters. The main advantage of using a MCS for classification is that the system is able to operate without the database, once the MCS is trained.

The experimental results show that the proposed approach yields a higher performance than other reported results on UBIRISv1 dataset. With a feature size of only 360 components, the proposed system is suitable to be deployed on mobile or embedded devices.

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